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Does Supported Employment Work?

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Abstract

Providing employment-related services, including supported employment through job coaches, has been a priority in federal policy since the enactment of the Developmental Disabilities Assistance and Bill of Rights Act in 1984. We take advantage of a unique panel data set of all clients served by the SC Department of Disabilities and Special Needs between 1999 and 2005 to investigate whether job coaching leads to stable employment in community settings. The data contain information on individual characteristics, such as IQ and the presence of emotional and behavioral problems, that are likely to affect both employment propensity and likelihood of receiving job coaching. Our results show that unobserved individual characteristics and endogeneity strongly bias naive estimates of the effects of job coaching. However, even after correcting for these biases, an economically and statistically significant treatment effect remains.

JEL codes: J29, I38, J14
Key terms: Supported employment, job coaching, employment of the disabled

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1 Introduction

Providing employment-related services to individuals with developmental disabilities has been a priority in federal policy for the past twenty years starting with the Developmental Disabilities Assistance and Bill of Rights Act in 1984 (Re-authorized in 2000, it is referred as DAA from this point on.). The DDA encouraged the creation of state-level supported employment programs designed to help individuals with developmental disabilities find and retain paid employment in integrated settings in a community. Supported employment placements are thought to be cost-effective when compared to the alternative of providing other day services for adults, but there is little evidence to show whether these services are effective at achieving the stated policy goal of stable, paid employment in community settings. We take advantage of a unique panel data set from South Carolina to measure the extent to which employment gains by individuals who receive supported employment services can be attributed to the participation in the program. Our results show that program participants have attributes associated with greater employability such as higher IQs and lower incidence of emotional and behavioral problems. However, after controlling for observed and unobserved heterogeneity of participants and non-participants using propensity score matching, fixed effects and instrumental variables methods, we still find that supported employment has an economically and statistically significant positive effect on employment. Program participants experience on average a 20 percentage points increase in the probability of being employed for at least half of the following year in a job paying a non-trivial wage.

Supported employment, using job coaches, is a mechanism to achieve paid employment in integrated settings in the community for adults with severe disabilities (McGaughey, Kiernan, McNally, Gilmore and Keith, 1995; Wehman and Kregel, 1998; Rusch and Braddock, 2004). It is estimated that about 1.2% to 1.5% of adults in the

United States meet the criteria for having developmental disabilities as defined in the Developmental Disabilities Assistance and Bill of Rights Act of 2000 (Yamaki and Fujiura, 2002)[1]. Evidence suggests that employment in an integrated setting is associated with higher wages and opportunities to expand social networks; however, the majority of individuals with intellectual disabilities remains unemployed, underemployed, or employed in segregated workshops (Jones and Bell, 2003; Yamaki and Fujiura, 2002; Rusch and Braddock, 2004). According to the American Association on Intellectual and Developmental Disabilities (AAIDD), the average cost of a supported employment placement is $4,000, and half of all placements cost less than $3,000 per person. AAIDD compares this cost to the $7,400 annual cost of serving an individual in a day program. A simple comparison of the costs indicates that the supported employment is approximately 20-60 percent cheaper than other day services. While these studies mentioned above suggest job coaching is both affordable and effective, it is possible that some of the apparent benefits of job coaching are due to underlying differences between those who receive coaching and those who do not. Our study is the first to examine the effectiveness of job coaching while controlling for selection and existence of unobserved heterogeneity that may affect both job coaching and employment outcomes biasing the estimates of the effect job coaching.

We use unique panel data collected in South Carolina from 1999 to 2005 for all individuals receiving any service from the Department of Disabilities and Special Needs (DDSN). While the data we use may not be available in other states, the supported employment program in South Carolina is otherwise typical of such programs throughout

[1] Developmental disabilities are defined as mental and physical impairments originating in childhood that are likely to continue indefinitely and result in functional limitations in three or more "major life areas." These life areas include self-care, language, learning, mobility, self-direction, independent living, and economic self-sufficiency.

the U.S.[2] Supported employment services in South Carolina are provided to individuals with mental retardation by 38 not-for-profit service providers (Disability and Special Needs Boards, henceforth called "boards") that serve county or multi-county areas. Thus, we have variation in the availability of job coaches over time and across boards. The data also contain information on individual characteristics, such as IQ, the presence of emotional and behavioral problems, and whether the individual is living in a supervised setting. We describe the supported employment program and our data in more detail in the following two sections. In Section 4 we discuss our empirical approach and then present the results of our analysis in Section 5. To measure the effectiveness of job coaching, we consider three strategies to control for observed and unobserved differences between participants and non-participants: 1) propensity score matching models; 2) panel logit models with fixed effects; and 3) instrumental variable models with fixed effects. Our results are qualitatively consistent across models. All models show that job coaching significantly raises employment probability. Naive models that do not adequately control for differences between participants and non-participants overstate gains, but a strong significant job coaching effect remains even in models with instrumental variables and fixed effects. These results show that supported employment is successful at increasing employment in integrated settings for adults with developmental disabilities.

[2] The primary differences between SC and other states are two-fold. First, the procedures for entering and serving adults who want to work is clearly laid out in a state policy and procedures system, and second, there is annual reporting of those who are employed with and without a job coach, and those who lose their jobs. An annual report is sent to every DSN Board every year and details about individual experience is available.

2 Supported Employment in South Carolina

The South Carolina supported employment system is a centerpiece of the day services offered to individuals with mental retardation. Every county Disability and Special Needs (DSN) Board offers the program to the individuals they serve. Supported employment programs have four components: 1) assessing skills and developing a plan for achieving competitive employment; 2) identifying a job suitable for the individual; 3) placement and job-site training; 4) follow-up. Job coaching begins when a DDSN beneficiary is referred to a coach by her case manager. Following a referral, there may be period of instruction and assessment aimed at improving the client's general job skills and awareness of community-based employment opportunities. Once a specific job has been identified and a job coach assigned, the process is expected to last at least a year beginning with six months of on-site training followed by at least six months of follow-up in which the coach maintains monthly contact with the client. While independence and job stability are the goal, retraining and "follow along" may last for a year or more.

Finding a good match, according to our discussion with officials in the program, is a big part of the coaching process. Bad matches result in rapid turnover. Our measure of employment success, defined below, will be based on employment in the year following any receipt of job coaching services and will exclude employment for low pay or short duration. Jobs for low pay do not satisfy the policy objective of competitive employment in integrated settings (rather than sheltered workshops), and therefore we do not count them as successful program outcomes. Using a lag of job coaching status allows us to look at employment outcomes of stable nature and also controls for the possible endogeneity of job coaching status.

In South Carolina, 38 local boards provide supported employment services to individuals with mental retardation, and the programs may differ by board, particularly before 2003, when statewide standards for supported employment were put into place. Job coaches must have a high school degree or equivalent and pass state law enforcement checks, but are often inexperienced and lack formal training. Larger boards may have a job coach supervisor, while smaller boards may be supervised by a day services director at the board who has many other non-employment related responsibilities. Larger boards may also have developed a network of employer contacts that enables good placements, while smaller boards are more dependent on the job development skills of the individual job coach and the community ties of board members.

While boards may try to make job coaches available for everyone who would like one, only a fraction of working age adults served by the board receive job coaching in any year. Some families and individuals served by DDSN opt for non-vocational day services (including recreation and leisure activities) rather than job coaching. These options might be selected because the individual does not want to work, has had a unsatisfactory work experience, or the family is concerned about the logistics of employment which include planning for reliable transportation, a regular sleep schedule, and potential for unpleasant social experiences. The demand for supported employment services at each DSN Board is a function of the number of adults served by the Board, the reputation for success or failure that has developed, and the staff support of the program. Some DSN Boards have a waiting list of 10-20 individuals at any given time and other Boards have a difficult time recruiting participants. We do not have data on waiting lists, but officials at the DDSN tell us that waits between the referral and onset of supportive employment services have generally been declining over the period of our data.

We do not directly observe the process by which individuals are allocated to job coaches. Selection into job coaching may be based on observable characteristics recorded in the DDSN record available to us such as the DSN board identifier or individual characteristics such as IQ, age and emotional or behavioral problems. Our empirical strategy must also allow for the possibility that there are unobservable individual characteristics that affect both coaching and employment. We discuss this is more detail in Section 4.

One individual factor we do not observe (but job coaches and individuals do) is whether employment will affect disability benefits. Most adults with mental retardation are eligible and do receive SSI. Earnings from employment can result in lower SSI benefits if the individual's adjusted earnings are sufficiently large. Most working individuals with mental retardation do not reach the substantial gainful activity (SGA) standard, which translates to full-time work (37.5 hours per week) at $6.53 per hour. Individuals with mental retardation who work competitively, with or without supported employment are usually eligible to maintain their Medicaid benefits which include health insurance and disability related services. Although the SSA has policies and procedures to encourage employment of people who receive SSI, the SSA is a complex system which requires some knowledge of the procedures and a substantial level of persistence to navigate. South Carolina Service Coordinators are assigned to every individual who is eligible to receive services for mental retardation and they assist individuals and families to understand their entitlements and navigate the system. In most cases when supported employment services are offered to an individual, the first discussion focuses on the implications for their SSI benefits.

3 Data and Variables

The data consist of individuals in South Carolina who have mental retardation and are clients of one of the 38 disability boards in South Carolina at any time between years

1999 and 2005.[3] To be included, an individual must be between 21 and 65 years of age (inclusive) during the year and have an IQ score above 26 and below 75. Individuals whose primary diagnosis is autism are excluded. Because there are very few individuals whose race is not identified as African American or white in the data, these individuals are also excluded. Over all seven years, there are 62,826 person-year observations. Descriptive statistics for the sample are shown in Table 1. About half (51%) of the sample is African American, and just under half (46%) of the sample is female. The average age and IQ are, respectively, 37.7 and 50.4. About 24% of the sample has some emotional or behavioral problems reported, and about the same percent live in a supervised setting. Table 1 also provides descriptive statistics separately for individuals who receive some job coaching and those who do not. On average, the job coached group consists of individuals who have higher IQ's (54.6 versus 49.7) and who are younger (35.82 versus 38.09). Job coached individuals are also more likely to be African American (55% versus 51%), male (56% versus 53%), and have no emotional or behavioral problems (25% versus 19%).

Job coaching typically consists of 6 months of on-site training and at least 6 months of follow-up. Our goal is to see whether coaching enables the individual to continue working after the coach has left the job site (but may still be offering continued support via monthly phone calls or visits). Hence we measure the effect of job coaching in year $t-1$ on the probability of employment in the subsequent year t. Because this requires 2 years of observation, we can model employment outcomes for 6 years (2000-2005). We construct an (unbalanced) panel of employment outcomes that includes an individual in year t whenever his history is observed in the previous year. The one exception is that individuals who were not observed in the data in $t-1$ were included and classified

[3] The data are stripped of personal identifiers and are part of an ongoing system of surveillance of employment. The employment surveillance system has university IRB approval.

as not having a job coach in $t-1$. This includes individuals who did not receive any services from DDSN (including job coaching) in $t-1$ and individuals who turned 21 in t.

Table 1. Descriptive Statistics for the Pooled Sample and by Job Coaching Status

	Pooled Sample		Not Job Coached		Job Coached	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Job coached	0.14	0.35				
Employed	0.16	0.36	0.09	0.28	0.56	0.50
Wages	118.35	66.17	101.87	60.50	134.14	67.52
County unemployment rate	6.11	2.30	6.15	2.30	5.83	2.26
IQ score	50.36	13.18	49.67	13.29	54.62	11.56
Percent job coached by the board	0.15	0.08	0.14	0.07	0.18	0.08
Emotional problems	0.24	0.43	0.25	0.44	0.19	0.39
Supervised	0.28	0.45	0.27	0.44	0.31	0.46
Age	37.77	11.43	38.09	11.62	35.82	9.92
Black	0.51	0.50	0.51	0.50	0.55	0.50
Female	0.46	0.50	0.47	0.50	0.44	0.50
	N=62,826		N=54,051		N=8,775	

Since supported employment is intended to facilitate stable employment in integrated settings (rather than sheltered workshops), we screen for employment in jobs with very low pay or very short duration. For the purposes of this study, employment is defined as earning at least $50 per week for 23 weeks or more (see, for example, Howarth et al., 2006; Pierce et al., 2003; Moran et al., 2002). Because our data does not differentiate between on-going on-site coaching, follow-up contact, and any re-training that occurs if there are job changes, we utilize a bivariate measure of job coaching (some or none) in year $t-1$.

About 15.5% of the sample is employed in any given year, but as shown in Table 2, this varies from a high of 20% in 2000 to a low of 11% in 2004. The overall labor market conditions worsen during the sample period with the average county unemployment rate rising from the lowest point of 3.82% in 2000 to 7.3% in the 2005. Mirroring these employment trends, the probability of receiving job coaching also falls during the period, from over 16% receiving job coaching at the beginning of the sample to only 10% by the end. This decrease in job coaching may be attributed to tightening state budgetary constraints, but may also reflect better accounting of job coaching hours due to an increase in auditing efforts. The reduction in job coaching at the individual level is also seen when aggregated to the disability board level. Of those receiving any services from a given board, the percent receiving job coaching services has declined from 18% to 11% over the sample period.

Table 2. Means of Employment and Job Coaching Variables by Year

	1999	2000	2001	2002	2003	2004	2005
Job coached	0.16	0.16	0.17	0.15	0.14	0.12	0.10
	(0.37)	(0.36)	(0.37)	(0.35)	(0.35)	(0.32)	(0.30)
Employed	0.15	0.18	0.20	0.16	0.18	0.11	0.12
	(0.36)	(0.39)	(0.40)	(0.37)	(0.38)	(0.32)	(0.32)
Wages (if employed)	122.71	116.17	117.97	120.61	121.51	112.52	115.84
	(64.97)	(63.95)	(63.72)	(65.93)	(72.44)	(64.31)	(66.45)
County unemployment rate	4.65	3.82	5.64	6.34	7.17	7.29	7.32
	(2.55)	(1.15)	(1.75)	(1.75)	(2.03)	(1.91)	(1.88)
Percent job coached by the board	0.18	0.17	0.17	0.16	0.15	0.13	0.11
	(0.07)	(0.07)	(0.08)	(0.09)	(0.08)	(0.06)	(0.05)
Sample size	8356	8691	7840	8812	9156	9783	10188

*Standard deviations shown in parentheses

4 Model and Estimation

4.1 Model

In the canonical model of employment, a person is employed if he is offered a job with a wage greater than his reservation wage. Thus, any analysis of employment probability should consider all factors that affect the wage offers in the market and the reservation wage of the individual. Recall that for this study a person is considered to be employed if they are working for at least 23 weeks in a given year and earning at least 50 dollars per week. Given this definition of employment, individuals who are working for very low pay or for short periods of time are classified as unemployed. Hence, our focus is on measuring the extent to which job coaching affects the likelihood of finding a job for a meaningful period of time at a non-trivial wage in integrated settings. We hypothesize that the probability of employment will depend on socio-demographic factors that affect the reservation wage and the returns in the labor market.

The model we are using is a standard employment model specified simply as follows

$$Y_{it} = X_{it}'\beta + \epsilon_{it}$$

where Y_{it} is i's employment status at time t, X_{it} consists of a vector of socioeconomic and demographic characteristics of the individual, β is a coefficient vector to be estimated, and ϵ_{it} is a matrix of individual and time-varying shocks. The X_{it} vector includes a constant and individual demographic characteristics, such as age, gender, race, as well as several variables typically unavailable to the econometrician, such as IQ, an index of emotional and behavior problems, and an indicator for living in a supervised residence. Characteristics of the local labor market and an indicator for the disability board are also included. Of particular interest is the indicator variable for whether or not the individual received job coaching in the year prior to the one for which we observe the employment outcome. Our goal is to measure the extent to which job coaching increases employment propensity.

If job coaches are assigned randomly, then we could easily estimate the effects of job coaching by comparing the probability of employment across those who received job coaching and those who did not. However it is much more likely that the assignment process was not random and that there is correlation between the factors that led to the receipt of a job coach and the probability of employment. For example, individuals with emotional and behavioral problems may be less likely to receive job coaching, and *ceteris paribus,* less likely to be employed. Thus, our choice of model will depend on the assumptions about ϵ_{it}. We first estimate propensity score matching models (Rosenbaum and Rubin, 1985). If participation in job coaching is due to "selection on observables" and there is sufficient overlap between the support for the comparison group and program participants, then matching on propensity scores approximates the randomized assignment of experimental methods (Heckman, Ichimura and Todd, 1997). Specifically, we assume that the distribution of ϵ_{it} is the same for individuals who are matched on all observables other than job coaching. Following these estimates we consider the possibility of time-invariant unobserved characteristics that are potentially correlated with job coaching. If such fixed factors exist, we will have an omitted variable bias, and we have to consider a composite error term instead, that is:

$$\epsilon_{it} = \upsilon_{it} + \nu_i$$

The next step in our choice of model will depend on the assumptions about ν_i. We will estimate two versions: random effects and fixed effects. While random effects require that ν_i's are uncorrelated with X_{it}, fixed effects does not require this restriction.

Finally, we use an instrumental variables approach to correct for bias due to endogeneity of the participation decision. We use a two-stage approach with a linear probability panel model with individual fixed effects in the second stage. Linear models are easy to estimate and require less assumptions than a fully structural approach, but have the disadvantage of introducing heteroskedasticity and ignoring the bounds that estimated probabilities should lie between zero and one. To account for heteroskedasticity, we obtain standard errors by bootstrapping (with 1000 repetitions).

4.2 Results

A simple comparison of means for our sample (shown in Table 1 & Table 2 above) shows that supported employment is associated with a substantial increase in the likelihood of being employed. Over the entire sample period, about 16% of the sample receive coaching in any given year, and of those who have coaches, 56% are employed. For those who receive no coaching, only 9% are employed. Comparison of means also reveals differences between program participants and non-participants. On average, those who receive job coaching have higher IQs (54.6 vs. 49.7), have a lower incidence of emotional and behavioral problems (0.19 vs. 0.25), and live in areas with lower unemployment (5.8 vs. 6.1). To further explore differences between participants and non-participants, we begin with descriptive models of the job coaching assignment process. These estimates are of interest because they show whether or not the assignment of job coaching is correlated with the individual characteristics we can observe in our data. In addition, propensity models for job coaching are used in the first stage of the matching models.

4.2.1 Estimates of Job Coaching Probability

Table 3 reports the results for panel logistic models of the propensity for job coaching with random effects and fixed effects. While probit models offer ease of interpretation, there is no sufficient statistic for conditioning fixed effects out of a probit likelihood. Hence, we report conditional logit models throughout. Our preferred specification includes both DSN board and year fixed effects.

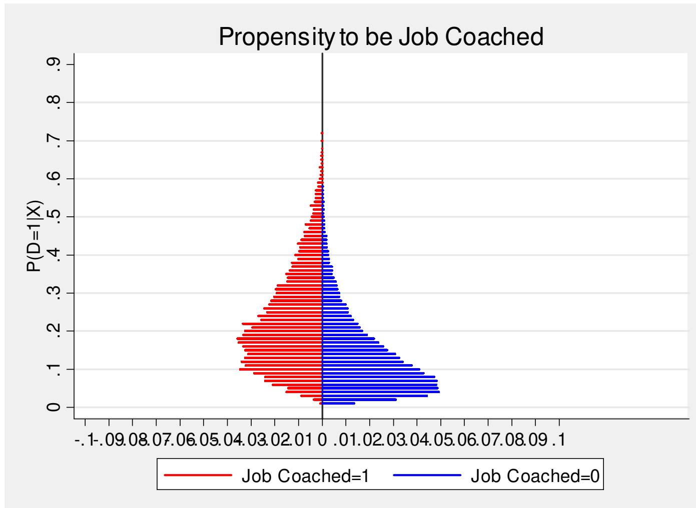
Table 3: Models of Job Coaching						
Dependent variable = Job Coached						
	RE	FE	RE	FE	RE	FE
percent of clients job coached	14.333	15.508	14.233	15.679	14.905	16.384
at the board level	(0.677)**	(0.773)**	(0.465)**	(0.837)**	(0.733)**	(0.856)**
age	0.358		0.353	0.476	0.357	0.465
	(0.023)**		(0.023)**	(0.28)	(0.023)**	(0.28)
age-squared	-0.005		-0.005	-0.009	-0.005	-0.009
	(0.000)**		(0.000)**	(0.001)**	(0.000)**	(0.001)**
female	-0.327		-0.323		-0.327	
	(0.083)**		(0.083)**		(0.083)**	
black	0.346		0.397		0.343	
	(0.088)**		(0.085)**		(0.088)**	
IQ score	0.065		0.063		0.065	
	(0.003)**		(0.003)**		(0.003)**	
emotional problems	-0.861		-0.855		-0.86	
	(0.101)**		(0.100)**		(0.101)**	
supervised	1.441	1.093	1.396	1.123	1.442	1.155
	(0.097)**	(0.212)**	(0.096)**	(0.213)**	(0.097)**	(0.219)**
unemployment rate	-0.010	-0.012	0.001	0.020	0.004	0.020
	(0.016)	(0.018)	(0.018)	(0.034)	(0.028)	(0.035)
constant	-15.915		-15.799		-16.086	
	(0.686)**		(0.492)**		(0.689)**	
board dummies	YES	YES	NO	NO	YES	YES
year dummies	NO	NO	YES	YES	YES	YES
number of observations	50401	9566	50401	9566	50401	9566
number of individuals	11004	1799	11004	1799	11004	1799
Standard errors in parentheses. * significant at 5% ** significant at 1%						

The results across models are qualitatively similar and show that many of the factors we would expect to influence a person's decision to enter the labor market are also associated with whether an individual participates in supported employment. Age has a non-linear effect on job coaching, with smaller increases in the likelihood of participation as age increases. Women are less like to be engaged in supported employment, while African Americans are more likely. Having a higher IQ and an absence of emotional and behavioral problems increases the likelihood of receiving job coaching. Participating in the program is not associated with variations in the county unemployment rate. Job coaches may have lower cost of serving individuals who live in supervised conditions, and so it is not surprising that this factor is associated with a significant increase in the likelihood of participation. These results suggest possible sorting on gains and reinforce our concerns about bias in estimating the effects of job coaching due to observed and unobserved heterogeneity.

The regressions reported in Table 3 also include a variable that is our candidate instrument for the instrumental variable analysis that follows: percent of board clients who receive job coaching in a given year. This variable measures the availability of job coaching, and we expect it to be positively correlated with individual propensity for job coaching. We defer a full discussion of its potential to be a good instrument below, but note here that passes the first test with a strong statistically significant effect on propensity to be job coached in the expected direction.

4.2.2 Propensity Score Matching

We begin the analysis of the effects of job coaching with propensity score matching models (PSM). Program participants are matched to "comparable" non-participants, and any difference in outcome is attributed to the program. The goal of PSM is to create a randomized trial on the pseudo subpopulation of the matched sample (Rosembaum and Rubin, 1985). The advantage of PSM is that we do not need to make parametric assumptions about the underlying relationships, but we do need to assume that the only selection operating on program participation is "selection on observables". To be more precise, let the indicator variable $D = 1$ if an individual actually participated in the program and denote the probability of employment if exposed to job coaching or not as $P(Y_1 = 1|D = 1)$ and $P(Y_0 = 1|D = 0)$, respectively. In our data, we observe these, but not the counterfactuals of what would have happened to participants had



they not participated, $P(Y_1 = 1|D = 0)$, or to nonparticipants had they participated, $P(Y_0 = 1|D = 1)$. For example when we want to measure the effect of job coaching on the employment outcomes of the joached individuals we are trying to calculate

$$E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) = P(Y_1 = 1|D = 1) - P(Y_0 = 1|D = 1),$$

We can estimate $P(Y_1 = 1|D = 1)$ since we have this information in our data. However, we do not observe $P(Y_0 = 1|D = 1)$ in our data and we need to construct a measure for it. PSM requires the assumption that all differences between the actual participants and nonparticipants are captured by the observables X. That is, once we control for the X′s all differences in terms of the employment outcomes of the "matched" individuals is due to the job coaching.

Propensity scores are estimated in the first step using logistic regression, and then participants are matched to nonparticipants using local linear regression with a tricube kernel (default bandwidth = 0.06). As Figure 1, shows there is a great deal of overlap of participation probabilities controlling for the observed characteristics of treated and nontreated groups, which makes this sample very suitable for matching analysis. Bootstrapping is used to obtain standard errors for the estimated average treatment effect on the treated. We stratify by year and also estimate with a pooled cross section of all the data. Estimation is done in STATA using PSMATCH2 (Leuven and Sianesi, 2002). We perform sensitivity analysis for the pooled sample by varying kernel bandwidth (default is 0.06, comparison is 0.02) and using a restricted set of regressors in estimating the propensity score. We restrict matches to a common support and report the number of unmatched individuals to see whether this is sensitive to bandwidth or specification. The results are reported in Table 3.

The average treatment effect on the treated is given by the difference in employment probability for the treatment and control groups. We find the estimated average treatment effects to be large, positive and significant in every specification. In the pooled data, the ATT for the matched sample is smaller than that of the unmatched sample, but we still find that those who are coached are over four times more likely to be employed than those who are not. The results are not sensitive to bandwidth or specification. A drawback of the pooled cross section results is that they do not take into account the fact that we have multiple observations over time on individuals. To eliminate the problem of multiple measures, we stratify by year. Analysis of the stratified samples shows that the ATT is positive in every year but decreasing over the period from a high of 0.531 in 2000 to a low of 0.279 in 2004. The variation in ATT corresponds to fluctuations in average employment, and shows that job coaching is effective even in *lean years* when employment is down.

Table 4: Propensity Score Matching Models of the Effects of Job Coaching on Employment

Year	Propensity Score Model		Had Coach	No Coach	Difference	St.Err.
		Pooled Data				
Pooled	Full Model	Unmatched	0.534	0.109	0.425	0.004
		ATT	0.534	0.120	0.413	0.005
		On-support n=	7,435	50,480		
		Off-support n=	1	63		
Pooled	Full Model (Bandwidth=0.02)	Unmatched	0.534	0.109	0.425	0.004
		ATT	0.534	0.121	0.413	0.006
		On-support n=	7,435	50,480		
		Off-support n=	1	63		
Pooled	Restricted Model	Unmatched	0.534	0.109	0.425	0.004
	(age, female, IQ, emot)	ATT	0.534	0.119	0.415	0.006
		On-support n=	7,436	49,845		
		Off-support n=	0	698		
		Stratified by Year				
2000	Full Model	Unmatched	0.653	0.107	0.546	0.010
		ATT	0.653	0.121	0.531	0.016
		On-support n=	1,301	6,520		
		Off-support n=	4	93		
2001	Full Model	Unmatched	0.647	0.111	0.535	0.011
		ATT	0.647	0.125	0.521	0.012
		On-support n=	1,274	6,457		
		Off-support n=	2	81		
2002	Full Model	Unmatched	0.558	0.094	0.465	0.010
		ATT	0.559	0.101	0.458	0.014
		On-support n=	1,287	6,701		
		Off-support n=	1	51		
2003	Full Model	Unmatched	0.549	0.116	0.433	0.011
		ATT	0.549	0.125	0.424	0.017
		On-support n=	1,246	6,879		
		Off-support n=	0	166		
2004	Full Model	Unmatched	0.370	0.082	0.288	0.010
		ATT	0.370	0.091	0.279	0.013
		On-support n=	1,202	7,603		
		Off-support n=	0	36		
2005	Full Model	Unmatched	0.397	0.089	0.308	0.010
		ATT	0.397	0.097	0.300	0.016
		On-support n=	1118	7,973		
		Off-support n=	1	137		

Using PSM to construct a random pseudo sample does not wash away the estimated gains from participation. This suggests that the difference in observables between treated and non treated individuals has a relatively small effect on the estimated effects. Our concern about differences in unobservables is not addressed by standard PSM methods. Moreover, standard PSM techniques do not take advantage of the longitudinal nature of our data. Heckman, Ichimura and Todd (1997) have shown that traditional matching methods may have significant bias if there are differences in the way outcomes and characteristics are measured for participants and non-participants or if the economic environment is not similar for both. Since we observe individuals for up to 7 years in our data, we move on to full panel data methods that allow us to use all data from each individual in controlling for time-invariant unobservable factors.

4.3 Estimates of Employment Probability

Table 5 presents the results of conditional logit panel regressions with random effects (RE) and fixed effects (FE) in the first two columns. The FE model is our preferred specification because it allows for correlation between ν_i's and X_{it}, but we report RE estimates, too. As expected, the RE results show that having a higher IQ, better local labor market conditions, or no reported emotional and behavioral problems raises the odds of having a stable, high-wage job. Above we found that individuals in supervised housing conditions are more likely to be job coached, and, other things the same, these individuals are also more likely to be employed. We also find that being female or white is associated with a reduced likelihood of employment, and that age increases the likelihood of employment at a decreasing rate. Having a job coach has a strong and significant effect on the probability of employment in both the RE and FE, but the effect is much smaller in the preferred FE specification. Looking at the odds ratios from the logit model shown towards the bottom of the table, we see that the odds of employment are increased by a factor of 1.5 when an individual has received job coaching in the preceding year. The estimated odds ratio is 5 is the RE specification and over 10 in the matching model (odds ratio for the pooled cross section PSM is $\frac{\frac{0.534}{1-0.534}}{\frac{0.120}{1-0.120}} = 10.85$). These results show that failing to allow for correlation between the unobservable individual specific error term and the observable individual characteristics results in a substantially overestimated effect of the benefits of the job coaching program. That said, even after controlling for unobserved, time-consistent differences across individuals, the odds ratio for job coaching remains economically significant at around 1.5. That is, participants in supported employment are about one and a half times more likely to be working in stable, high wage jobs to their non-job coached counterparts.[4]

The above analysis has shown that our results are sensitive to whether and how we allow for unobserved, time-consistent differences across individuals. The coefficient in the RE specification is about three times that of the FE specification. Surprisingly, the precision of the estimate is unchanged across the two models, even though the conditional logit with FE is estimated on a smaller sample (roughly 16,000 observations from 2500 individuals for the fixed effects specification versus over 57,000 observations from 11,000 individuals for the random effects specification). This difference in sample size arises because the fixed effect model cannot use observations for which the dependent variable is unchanged over the course of the sample (that is, the always employed and never employed).

[4]We estimate all models using *STATA*. Because we consider a variety of specifications, we report the *STATA* command along with the estimation results. See Schaffer (2009) for details about XTIVREG.

Table 5: Panel Data Models

Dependent variable: Employed

Estimation Method	logistic panel regression with individual effects (using XTLOGIT)						two stage linear panel regression with individual effects (using XTIVREG)		
	RE	FE	RE	FE	RE	FE	FE	FE	FE
job coached	1.57	0.599	1.590	0.413	1.613	0.403	0.195◊	0.209◊	0.207◊
	(0.052)**	(0.052)**	(0.055)**	(0.056)**	(0.056)**	(0.056)**	(0.060)**	(0.059)**	(0.056)**
age	0.216	-0.05	0.220	0.402	0.225	0.402	0.013	-0.012	0.013
	(0.019)**	(0.039)	(0.019)**	(0.172)*	(0.019)**	(0.173)*	(0.012)	(0.004)**	(0.011)
age2	-0.003	-0.001	-0.003	-0.002	-0.003	-0.002	-0.000	-0.000	-0.000
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)	(0.000)	(0.000)
female	-0.546		-0.564		-0.564				
	(0.071)**		(0.073)**		(0.072)**				
black	0.478		0.602		0.487				
	(0.076)**		(0.074)**		(0.077)**				
IQ score	0.033		0.030		0.034				
	(0.003)**		(0.003)**		(0.003)**				
emotional problems	-0.792		-0.786		-0.794				
	(0.086)**		(0.087)**		(0.087)**				
supervised	0.884	0.755	0.814	0.754	0.845	0.700	0.047	0.043	0.044
	(0.081)**	(0.157)**	(0.082)**	(0.153)**	(0.082)**	(0.160)**	(0.016)**	(0.018)*	(0.017)**
Unemployment rate	-0.198	-0.01	-0.139	-0.001	-0.018	0.003	-0.004	0.001	-0.004
	(0.012)**	(0.02)	(0.016)**	(0.025)	(0.025)	(0.026)	(0.002)	(0.002)	(0.003)
constant	-8.469		-8.099		-9.706				
	(0.576)**		(0.421)**		(0.634)**				
Board dummies	YES	YES	NO	NO	YES	YES	NO	YES	YES
year dummies	NO	NO	YES	YES	YES	YES	YES	NO	YES
Instrument							percent job coached by the board		
Number of observations	57979	16426	57979	16426	57979	16426	50401	50401	50401
Number of Individuals	11268	2556	11268	2556	11268	2556	11004	11004	11004
Odds ratios	5	1.8	4.9	1.5	5	1.5			

◊ indicates that instead of observed job coaching status, fitted values are used

Standard errors in parentheses. * significant at 5% ** significant at 1%

Given these results and our strong *a priori* beliefs that there are some unobserved factors that effect both selection into job coaching and employment probability, we also consider an instrumental variables (IV) approach. Our strategy is also similar to Aakvik, Heckman and Vytlacil (2005) in seeking a measure of treatment availability that is correlated with participation in the program (vocational rehabilitation in their case), but does not affect employment probability other than through the effect of program participation. Aakvik, Heckman and Vytlacil (2005) have a direct measure of the length of the queue for entering the program that they use as their instrument. While we have no way of directly measuring how long individuals have to wait before entering the program, we do have a board-level measure of job coaching availability. This measures is the ratio of individuals receiving job coaching to clients registered to each disability board in each year. We have already seen in Table 3 that the percent of clients job coached at the board level is a statistically significant predictor of participation in supported employment. The IV-linear probability estimates are reported in the last three columns of Table 5. All our IV estimates pass the Kleibergen-Paap underidentification test. The coefficient estimate on job coaching has the same sign in all probability models, and is statistically significant at 1% level in all models.

5 Conclusions

Since the Developmental Disabilities and Assistance and Bill of Rights Act of 1984, increasing employment in integrated settings for individuals with developmental disabilities through supported employment has been a primary goal of federal policy. State level Supported Employment programs have been created across the nation and in these increasingly tight budgetary times, it is important to consider whether government funded programs achieve stated goals. In addition, this kind of analysis is essential in informing states about possible effects of program cuts of the sort that our study state, South Carolina, has experienced.

While evaluations of job coaching programs suggest that they are effective and cost-effective, previous studies do not adequately address endogeneity concerns. Our analysis using a unique seven-year panel data set from South Carolina (1999-2006) suggests that such concerns are warranted. We see that 56% of individuals with job coaches are working in the following year compared to 9% of those who are not job coached, but that those who receive coaching are also more likely to have favorable job characteristics such as higher IQs and an absence of emotional and behavioral problems. Using fixed effects and IV models to address endogeneity and unobserved heterogeneity washes away much of the effect of job coaching, but an economically and statistically significant effect remains. We find that job coaching increases the odds of employment at least by roughly 1.5 times.

Much work remains to be done to understand how job coaching programs may be best deployed. Our results indicate that observed and unobserved differences explain a large portion of the improvement in the probability of employment. Further research is needed to understand more about the process by which individuals are allocated to job coaching. While the focus of this paper is to measure the mean effects of the job coaching, we hope in further research to use new techniques to disaggregate the benefits of job coaching and find whether improved targeting would enhance program success.

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